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Review

Artificial Intelligence and Pediatrics: Synthetic Knowledge Synthesis

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Abstract: The first publication on the use of artificial intelligence (AI) in pediatrics dates back to 1984. Since then, research on AI in pediatrics has become much more popular, and the number of publications has largely increased. Consequently, a need for a holistic research landscape enabling researchers and other interested parties to gain insights into the use of AI in pediatrics has arisen. To fill this gap, a novel methodology, synthetic knowledge synthesis (SKS), was applied. Using SKS, we identified the most prolific countries, institutions, source titles, funding agencies, and research themes and the most frequently used AI algorithms and their applications in pediatrics. The corpus was extracted from the Scopus (Elsevier, The Netherlands) bibliographic database and analyzed using VOSViewer, version 1.6.20. Done An exponential growth in the literature was observed in the last decade. The United States, China, and Canada were the most productive countries. Deep learning was the most used machine learning algorithm and classification, and natural language processing was the most popular AI approach. Pneumonia, epilepsy, and asthma were the most targeted pediatric diagnoses, and prediction and clinical decision making were the most frequent applications.

Keywords: pediatrics; artificial intelligence; synthetic knowledge synthesis; bibliometrics; machine learning

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1. Introduction

Historically, the use of artificial intelligence (AI) in pediatrics dates back to 1984 to a publication introducing SHELP, a computer-assisted decision-making system that diagnosed inborn metabolic problems [1]. A rising need due to disparities between the healthcare workforce and pediatric patients, the growing complexity of pediatric data collected, the rising costs of healthcare systems, and the need for increased efficiency and effectiveness, on one side, and the fast development of healthcare technology combined with the availability of big data and new treatments, on the other side, has triggered the increased popularity and use of AI in pediatrics.

As a result, the number of peer-reviewed publications concerning AI in pediatrics largely increased following the accelerated rates of scientific knowledge doubling observed in other scientific disciplines. In combination with new web-based approaches to scholarly communication, faster cycles of technological innovations in AI, and Open Science movements, these phenomena have increased the availability of research studies in digital formats, providing ample opportunities to synthesize research evidence automatically. Following the above, Kokol et al. [2] seized this opportunity and developed a novel synthetic knowledge synthesis methodology (SKS). SKS is founded on the triangulation of descriptive bibliometrics, bibliometric mapping, and content analysis, thus integrating quantitative and qualitative aspects of knowledge synthesis. In this manner, SKS extends the traditional bibliometric analysis with machine learning pattern recognitions of the structure, associations, and content of sets of research publications. As such, SKS overcomes some of the weaknesses of traditional knowledge synthesis approaches; for example, it requires fewer resources and can be conducted semiautomatically on big-data-size corpora of thousands or even tens of thousands of publications and not only on small manually selected samples of a few publications. This makes knowledge synthesis reproducible, holistic, and less prone to bias.

The aim of this SKS study was to answer the following research questions:

- What is the volume and scope of the research on the use of AI in pediatrics?
- What are the volume and dynamics of the production of the research literature on AI use in pediatrics?
- How is research geographically distributed?
- Which information titles informing the scientific community are the most prolific and enable prospective authors to present their research to the widest audience?
- Which funding bodies sponsoring research on AI in pediatrics are the most prolific?
- What are the most prolific research themes?
- What are the most used AI algorithms and approaches?
- What are the most targeted pediatric diagnoses?
- What are the most used AI applications in pediatrics?
- What are the patterns of international research co-operation?

2. Methods

The main two advantages of bibliometrics are domain independence and that it enables analyses of large quantities of publications. Descriptive bibliometrics are used to analyze the spatial and productivity characteristics of a corpus of publications [3–5]. The second component of SKS, bibliometric mapping, visualizes and maps the relationships and associations between units (terms, authors, source titles, countries, and similar topics) into a research landscape using text mining and clustering algorithms. A research landscape is a network of the above types of nodes in which links denote various relations, the proximity similarity, and the node size popularity. Clusters represent strongly associated units. Research landscapes can also be shown in overlay modes, where overlays reflect timelines, citation density, etc. [6]. The third component of SKS is a content analysis [7], a resourceful approach which, in our case, was used for a qualitative analysis of phenomena contained in research publications to obtain their objective and holistic descriptions in the forms of categories and themes. In this study, SKS was performed in the following way:

- Research publications on the topic of interest were extracted from the Scopus bibliographic database using an appropriate search string representing the set research questions.
- A descriptive bibliometric analysis was performed using Scopus's built-in functionality.
- Author keywords were used as meaningful units of information, and bibliometric mapping was executed using VOSViewer [6]. Next, using an inductive content analysis, the node size, links, and proximity between meaningful units in individual clusters and their borders were analyzed to form categories and identify themes.
- Author keywords were used as meaningful units of information, and VOSViewer was used to analyze their frequencies. A deductive content analysis with the preconceived categories of machine learning algorithm, AI approach, pediatric diagnosis, and application in pediatrics was performed.
- Country names were used as meaningful units of information, and citation density labeled bibliometric mapping was executed using VOSViewer. Next, the overlay color, node size, and links between countries were analyzed to identify country cooperation and the citation density of the various countries' publications.

Scopus (Elsevier, The Netherlands) was chosen as the source bibliographic database because it is considered reliable and authoritative [8] and is the largest abstract and citation database of the research literature, including almost 50,000 source titles from more than 12,500 publishers. Most of the indexed content is peer-reviewed. It offers advanced analytics services and enables 20,000 records to be exported in one piece, which offers considerable support for a bibliometric analysis.

To form a suitable corpus of publications a search query was constructed using the recommendation provided by Farooq et al. [9], namely, taking into account search strategies used in previous review papers and author keywords found in research papers concerning AI and machine learning. After experimenting with different search strings, taking into account the recall information retrieval metric, the following search query was used (recall = 0.95):

TITLE-ABS-KEY((“artificial intelligence” OR “machine learning” OR “deep learning” OR “intelligent system” OR “support vector machine” OR (“decision tree” AND (induction OR heuristic)) OR “random forest” OR “Markov decision process” OR “hidden Markov model” OR “fuzzy logic” OR “k-nearest neighbour” OR “naive Bayes” OR “Bayesian learning” OR “artificial neural network” OR “convolutional neural network” OR “recurrent neural network” OR “generative adversarial network” OR “deep belief network” OR “perceptron” OR “natural language processing” OR “natural language understanding” OR “general language model”) and (pediatrics OR paediatrics))

The search was performed in an advanced mode on titles, keywords, and abstracts without any inclusion or exclusion criteria on the 29 November 2023.

3. Results and Discussion

The resulting corpus contained 4116 publications, of which there were 2691 original articles, 652 conference papers, 388 review papers, 119 editorials, 110 short papers, notes, 69 conference reviews, nine book chapters, 16 errata, and four retractions.

3.1. Spatial Distribution of Research

3.1.1. Volume and Dynamics of Research Literature Production

The first publications appeared in 1998. Between 1998 and 2004, research production was modest (with a maximum of six articles), followed by a slightly positive linear trend until 2015 (Figure 1). The year 2016 saw exponential growth in research productivity that lasted until 2023, when the number of publications peaked at 996 articles. The exponential trend starting in 2016 might be a consequence of the release of IBM Watson and its use in healthcare [10]. In addition, around 2014, deep learning began to become popular in medicine [11]. However, we must take into account that the production growth reflected in Figure 1 might also be attributed to the coverage expansion of bibliographic datasets [12].

3.1.2. Geographical Distribution of the Research Literature Production

Among 121 countries, the 10 most productive countries are shown in Table 1. Nine of them are members of the G20, and Spain is among the most economically developed countries with an efficient health system, indicating a regional concentration of research in more developed countries. The above list of countries compares to the Scimago list (Elsevier, Amsterdam, The Netherlands) of the most productive countries in medicine. The only exception is Japan, which is not on our list of the top ten most productive countries but ranks fifth on the Scimago list. The reason for this might be that Japan is the healthiest country for children, according to the World Health Organization [13]. It is interesting to note that the internationalization of research also increased during the studied period. Namely, in the period from 1987 to 1999, 16 countries were involved in publishing research on AI in pediatrics, while in the next decade, this number grew to 34 countries and reached 118 countries in the last period.

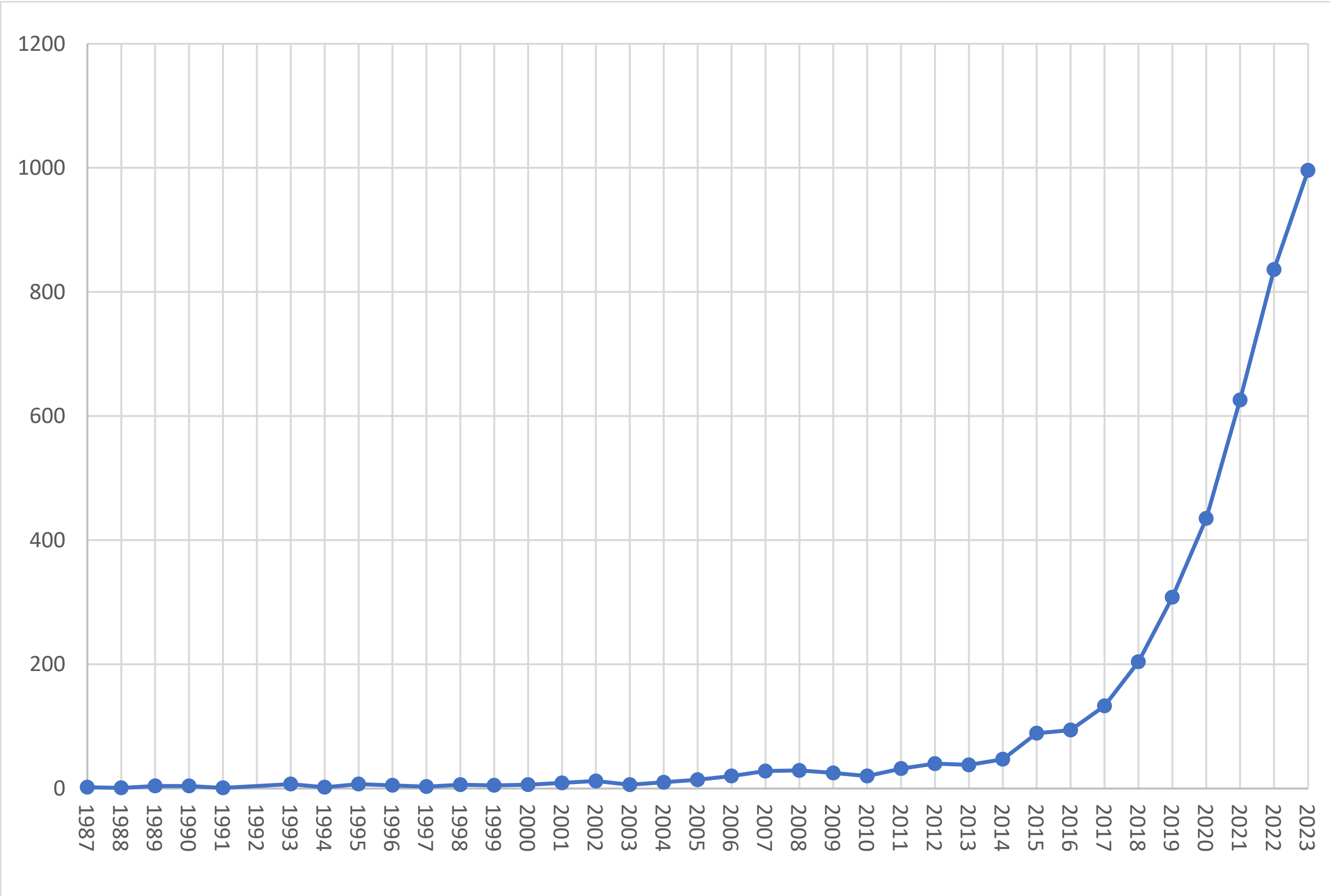

Figure 1. Dynamics of the research literature production.

Table 1. The ten most productive countries.

Country	Number of Publications
United States of America	1786
China	531
Canada	335
United Kingdom	330
Germany	211
India	185
Italy	179
Spain	146
Australia	142
South Korea	132

Among 3950 institutions, the most prolific were Harvard Medical School, USA (n = 151), the Children's Hospital of Philadelphia, USA (n = 132), Boston Children's Hospital, USA (n = 132), the University of Toronto, Canada (n = 121), the Hospital for Sick Children, Toronto, Canada (n = 112), Stanford University, USA (n = 109), and Cincinnati Children's Hospital Medical Center, USA (n = 912). During the period from 1987 to 1999, authors from 587 institutions published research on AI in pediatrics. During the next decade, this number grew to 1417 institutions, and in the last period, the number grew to 3128 institutions. At the same time increments, the number of authors increased from 1562 to 3341 and to 5837 in the last decade.

3.1.3. Prolific Source Titles

Publications have been published in 952 journals. Table 2 displays the titles of the 10 most prolific source titles. Most of the journals are categorized into the first quarter (Q1) of journals with respect to the Scopus SJR impact factor. The impact factor values range from 0.21 to 1.67. The H-index, another important indicator of journal impact, ranges from 60 to 404. These statistics indicate that publications in the fields of AI in pediatrics are published in well-recognized and influential source titles, indicating the importance of the topic under consideration.

Table 2. Titles of the most prolific sources.

Source Title	Number of Publications	Impact Factors (SJR—Scopus 2021)	H-Index	Quarter
Lecture Notes in Computer Science	155	0.32	209	Q3
Frontiers in Pediatrics	70	0.80	62	Q1
Scientific Reports	67	0.97	282	Q1
Pediatric Radiology	65	0.65	95	Q2
Progress in Biomedical Optics and Imaging Proceedings of SPIE	50	0.21	60	N/A
PloS ONE	48	0.89	404	Q1
Pediatric Critical Care Medicine	40	1.42	100	Q1
Pediatric Research	34	1.04	165	Q1
IEEE Journal of Biomedical and Health Informatics	30	1.67	146	Q1
Computer Methods and Programs in Biomedicine	29	1.12	124	Q1

3.1.4. Most Prolific Funding Bodies

Among 402 funding bodies, the most prolific were the National Institutes of Health, USA (n = 517), the National Natural Science Foundation of China (n = 202), the U.S. Department of Health and Human Services (n = 163), the National Center for Advancing Translational Sciences, USA (n = 108), the National Heart, Lung, and Blood Institute, USA (n = 95), the National Cancer Institute, USA (n = 79), the Eunice Kennedy Shriver National Institute of Child Health and Human Development (n = 77), the National Science Foundation (n = 72), the National Institute of Child Health and Human Development (n = 66), and the U.S. National Library of Medicine (n = 59). It is notable that the 10 most productive funding institutions come from only two countries, namely, the USA and China. It is also interesting to note that 47.4% of the papers are funded, which is significantly more than in many other research areas [14].

3.2. Content Analysis

3.2.1. Inductive Content Analysis: Most Prolific Research Themes

An inductive content analysis resulted in five themes and ten categories. The author keyword landscape is presented in Figure 2, and the SKS results are presented in Table 3. An overview of the influential recent research is presented below.

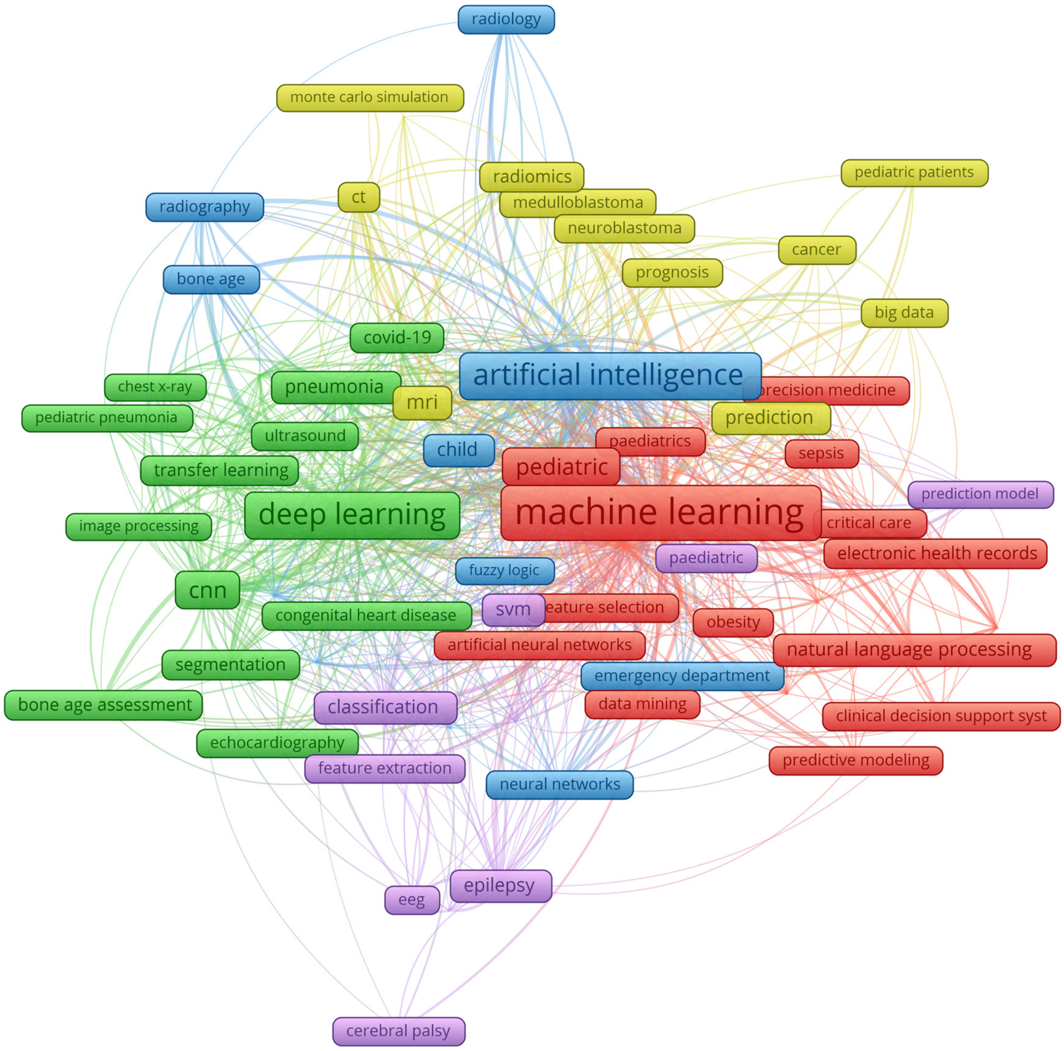

Figure 2. Authors' keyword map for keywords appearing in 15 or more publications.

Table 3. Representative author keywords, and categories and themes identified in research concerning AI use in pediatrics (represented by the number of keywords in a cluster, and the numbers in parentheses represent the frequency codes).

Color	Representative Author Keywords (Codes)	Categories	Themes
Green (n = 17)	Deep learning (431); CNN—convolutional neural network (152); pediatric pneumonia (n = 56); transfer learning (n = 54); bone age assessment (47); COVID-19 (43); congenital heart diseases (n = 29)	Deep learning with convolutional networks for complex decision making about bone age assessments and pneumonia; segmentation of echocardiography images into congenital heart diseases	Analyzing complex signals using deep learning
Red (n = 22)	Machine learning (758); pediatrics (464); prediction (n = 61); natural language processing (n = 60); electronic health records (n = 58); clinical decision support (53); asthma (39); critical care (32); data mining (26); artificial neural networks (25); sepsis (25)	Machine learning on electronic health records for prediction and critical decision support in asthma and sepsis; natural language processing of electronic health records; big data analyses for pediatric cancer patients	Critical clinical decision making and prediction using machine learning and natural language processing

Table 3. *Cont.*

Color	Representative Author Keywords (Codes)	Categories	Themes
Violet (n = 11)	Classification (73); SVM—support vector machines (63); epilepsy (57); artificial neural networks (32); feature extraction (28); cerebral palsy (17)	Segmentation, feature selection, and classification of EEG and MRI signals; seizure detection in epilepsy and cerebral palsy	MRI and EEG analyses in seizure detection in epilepsy and cerebral palsy
Blue (n = 14)	Artificial intelligence (420); children (188); radiology and radiography (50); autism spectrum disorder (34); bone age (30); emergency department (20)	Artificial intelligence-based processing of radiography and radiology outputs for assessing bone age; diagnosis of autism spectrum disorder using artificial intelligence	Using artificial intelligence for diagnosis
Yellow (n = 13)	MRI—magnetic resonance imaging (48); blastoma (46); CT—computer tomography (44); radiomics (41); cancer (24); Monte Carlo simulation (16)	Analysis of CT and MRI images for blastoma prognoses	Radiomics in pediatric cancer treatment

Analyzing complex signals using deep learning:

In several interesting pediatrics applications, deep learning was used to reduce noise in CT images, thus improving their quality and consequently enabling reductions in radiation doses [15–17]. Additionally, deep learning was used in fracture detection in children [18], tumor burden assessments [19], and interpreting chest radiography [20].

Deep learning with convolutional networks for complex decision making about bone age assessment and pneumonia treatment:

Deep learning performed on radiographs using convolutional and regression networks has been used for bone age assessments as bone age is an important measure of skeletal growth and biological maturity, indicating possible disorders in children [21–24]. Chest X-ray radiographs are considered the best, but they are a very challenging imaging modality for early and optimal pneumonia diagnosis in children. To support diagnoses, an automated convolutional neural network-based transfer learning approach has been developed [25]. High accuracy in detecting pneumonia and classifying its viral and bacterial types has been achieved using Bayesian convolutional networks [26]. As an alternative method, a lung ultrasound can be used to diagnose community-acquired pneumonia in children; however, it must be performed by experienced physicians and is very time-consuming, so convolutional networks have been used to optimize the task [27].

Deep learning in congenital heart diseases:

Hiroki et al. [28] demonstrate how to achieve improved diagnostic accuracy of heart diseases in pediatric populations using a deep learning model comprising a convolutional neural network and long short-term memory to analyze electrocardiograms. In another study, the automated segmentation of four-dimensional MRI images using convolutional neural networks was used in diagnosing congenital heart disease in children [29]. An automated machine learning echocardiographic diagnosis focusing on mitral regurgitation identification showed that it may enable enhanced screening, early diagnosis, and improved outcomes in pediatrics [30].

Critical clinical decision making and prediction with machine learning and natural language processing:

Traditional machine learning and big data analyses in critical decision making were successfully used in an intelligent mobile application supporting decision making as to whether children should go out for physical activity and whether schools should be reopened to preserve children's psychological well-being during the COVID-19 pandemic [31]. Random forest and gradient boosting machine methods were used in AI to support the diagnosis, severity assessment, and management of appendicitis in children [32]. Machine learning has been used to predict the length of stay in pediatric UCI units [33]. A neural network combined with a gradient boosting classifier was successfully used to extract information from textual data to predict and triage patients for admission in pediatric emergency departments [34]. Additionally, a machine learning-based system to improve the efficiency of pediatric emergency departments, focusing on minimizing time for decision making and predicting the need for clinical testing, was developed and used, streamlining the triaging process by almost 23% [35].

Machine learning using electronic health records for predication and critical decision support in asthma and sepsis:

Decision trees were successfully used to associate demographic features with allergic outcomes during the allergic march to assess the possibility of allergy transfer to asthma in children with respect to race [36]. Decision trees were also used to explore the relationship between various risk factors and childhood asthma [37]. Neural networks were used for a cough sound analysis to differentiate pneumonia from asthma [38]. Various traditional machine learning algorithms have been used to predict sepsis survival in infants with meningococcal septic shock based on gene expression changes and clinical features [39].

Natural language processing of electronic health records:

The emergence of electronic health records and AI-based natural language processing enabled the analysis of clinical data and offered new perspectives for the diagnosis and management of pediatric patients. Various new possibilities appeared, such as the diagnosis of rare diseases [40], predictions of childhood and adolescent obesity [41], epilepsy treatment [42], the prediction of infections [43], and the detection of child abuse [44].

Big data analysis for pediatric cancer patients:

Pediatric cancer is, fortunately, a rare disease; however, due to its low incidence, it presents a significant challenge in collecting enough data for analysis. Big data registry trials enable advancements in the study and treatment of pediatric cancers [45]. In combination with precision medicine, big data have demonstrated clinical benefits [46]. More precisely, big data analyses have been used in an acute lymphoblastic leukemia classification [47] and oncology risk assessment [48].

MRI and EEG analysis in seizure detection in epilepsy and cerebral palsy:

Segmentation, feature selection, and classification of EEG and MRI signals:

Support vector machines in combination with voxel-based morphometry were shown to be capable of classifying pediatric mesial temporal lobe epilepsy with hippocampal sclerosis with high accuracy [49]. In another study, deep learning was used for the classification of the type of cerebral palsy in newborns via analyzing functional MRI data [50].

Seizure detection in epilepsy and cerebral palsy:

The K-nearest neighbor approach was shown to be the best machine learning algorithm for detecting epileptic seizure activity in children when analyzing EEG signals [51]. Feature selection in a wavelet packet decomposed signal using a random forest algorithm was shown to improve seizure detection accuracy in detecting seizures [52].

Using artificial intelligence for diagnoses:

Artificial intelligence has been used to diagnose pediatric diseases for various purposes, such as auscultation like identifying heart conditions based on the analysis of an auscultation murmur [53], COVID-19 diagnoses [54], rare disease identification [55,56], and clinical decision support [57].

Artificial intelligence-based processing of radiography and radiology outputs for assessing bone age:

Various studies showed that artificial intelligence can be successfully used in bone age assessments in pediatric populations [58–60], for example, for hand wrist maturation assessments [61] and adult height predictions [62].

Diagnosis of autism spectrum disorder with artificial intelligence:

Convolutional neural networks were used to develop an automated facial expression recognition therapeutic tool on mobile devices for children with autism [63]. A method based on a radial basis function neural network was used to support the design and evaluation of educational toys for children with autism [64].

Radiomics in pediatric cancer treatment:

Radiomics has been successfully used in decision making concerning urological cancer in children, [65], neuro-oncology [66], and targeted cancer therapy [67].

Analysis of CT and MRI images for blastoma prognosis:

Machine learning analyses of computed tomography images were used for non-invasive predictions of *MYCN* amplification status in pediatric neuroblastoma patients [68,69], predicting the risk of recurrence [70] and identifying high-risk neuroblastoma [71].

3.2.2. Deductive Content Analysis of the Most Prolific Machine Learning Algorithms, Approaches, Pediatric Diagnoses, and Applications

The results of the inductive content analysis, including the 15 most prolific representatives of the preconceived categories of machine learning algorithms, AI approaches, pediatric diagnoses, and applications in pediatrics, are shown in Table 4. The most used machine learning algorithms are from the family of neural networks, followed by support vector machines, and naïve Bayes classifiers. The most frequently used AI approaches are classification, natural language processing, and text mining. AI is most frequently used to help children with pneumonia, epilepsy, COVID-19, and asthma. The most frequent applications are signal and image processing, prediction and computer-aided diagnosis, bone age assessments, decision making in critical care, and clinical decision making in general.

Table 4. The results of the deductive content analysis based on keywords emerging in five or more publications (the number in parentheses represents the number of publications in which a certain code emerges).

Machine Learning Algorithms	AI Approaches	Pediatric Diagnoses	Applications in Pediatrics
Deep learning (464)	Classification (95)	Pneumonia (71)	Prediction (146)
Convolutional neural network (196)	Natural language processing (60)	Epilepsy (70)	Clinical decision support (112)
Transfer learning (54)	Data and text mining (31)	COVID-19 (43)	Computer-aided diagnosis (86)
Support vector machine (51)	Feature selection and extraction (64)	Asthma (50)	Critical care (43)
Artificial neural networks (111)	Monte Carlo simulation (33)	Obstructive sleep apnea (12)	Signal and image processing (73)
Random forest (45)	Data augmentation (8)	Autism spectrum disorder (34)	Radiomics (41)
Fuzzy logic (16)	Big data (19)	Sepsis (35)	Computer vision (16)
Logistic regression (19)	Explainable artificial intelligence (10)	Cerebral palsy (17)	Triaging (11)
Decision tree (18)	Digital health (16)	Kidney diseases (16)	Anomaly detection (12)
Ensemble learning (15)	Expert systems (6)	Cancer (47)	Epidemiology (14)
Genetic algorithm (8)		Crohn's disease (12)	Length of stay (7)
Bayesian methods (10)		Cystic fibrosis (10)	Metabolomics (10)
		Mental health (12)	Quality improvement (12)
		Congenital heart disease (39)	
		Blastoma (50)	Severity of illness (9)

3.3. Research Cooperation

Country cooperation based on co-authorship is presented in Figure 3. As shown, 54 countries have published 10 or more publications. The United States (n = 52), the United Kingdom (n = 48), Spain (n = 44), Australia (n = 43), Germany (n = 43), Canada (n = 41), China (n = 41), France (n = 40), and Austria (n = 39) were the countries with the most intensive international collaborations. The n represents the number of countries with which a certain country cooperates.

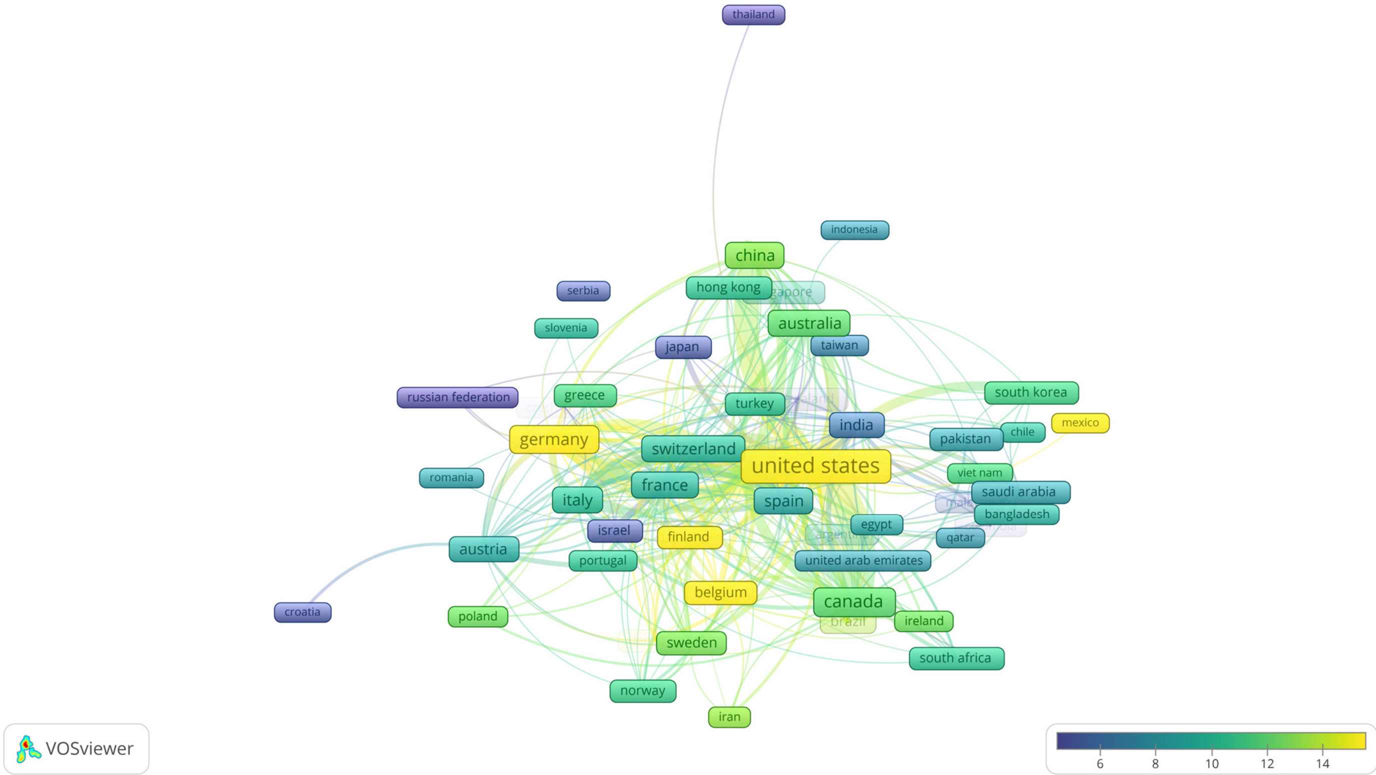

Figure 3. Country cooperation map based on co-authorships. The colors represent the average age of publications, and the rectangles represent the number of co-authorships with other countries. Countries with 10 or more publications are shown.

The most intensive bilateral cooperations existed between the United States and Canada (132 publications), between the United States and China (93 publications), between the United States and the United Kingdom (92 publications), between the United States and Korea (32 publications), and between the United States and Germany (56 publications). In Europe, the most intensive cooperations existed between Germany and the United Kingdom (n = 40), between Germany and Italy (n = 25), between Italy and the United Kingdom (n = 26), and between the Netherlands and Switzerland (n = 14). In other regions, notable cooperations existed between China and Hong Kong (n = 18), between Saudi Arabia and India with 12 publications, and between South Korea and China with 5 publications. The oldest average publication ages were found in Sweden, Ireland, Japan, and Poland, and the youngest were found in Singapore, Saudi Arabia, Pakistan, and South Korea.

The most cited publications were from the United States, Germany, Finland, Belgium, Mexico, and Brazil, and the least cited publications were from Thailand, Croatia, Serbia, Israel, Japan, the Russian Federation, and Malaysia (Figure 3).

3.4. Study Limitations

Like most, similar studies, this one also has some limitations. Its first limitation is that the analysis was performed only on publications indexed in Scopus. However, due to the fact that Scopus covers the largest and most complete set of information titles, the integrity of the data source is assured. Additionally, some parts of the study were qualitative, which might have resulted in a slight bias in research theme identification and naming. Finally, the funding information in Scopus might contain some inaccuracies [72], but this seems to have been reduced recently [73].

4. Conclusions

The landscapes uncovered in this study present multi-dimensional facets and different maps of the use of AI in pediatrics. The landscape reveals that an exponential growth in the literature production and research community was observed in the last decade. The United States, China, and Canada were the most productive countries, and Harvard Medical School, the Children's Hospital of Philadelphia, and Boston Children's Hospital were the most productive institutions. The most prolific funding bodies were the National Institutes of Health (USA), the National Natural Science Foundation of China, and the U.S. Department of Health and Human Services (n = 163). Deep learning, support vector machines, and artificial neural networks were the most used machine learning algorithms. Classification, natural language processing, and data and text mining were the most popular AI approaches. Pneumonia, epilepsy, and asthma were the most targeted pediatric diagnoses, while prediction, clinical decision support, and computer-aided diagnoses were the most popular AI applications. The five identified research themes were analyzing complex signals using deep learning, critical clinical decision making and prediction with machine learning and natural language processing, MRI and EEG analyses in seizure detection in epilepsy and cerebral palsy, using artificial intelligence for diagnoses, and radiomics in pediatric cancer treatment.

The above landscapes can help the research community solve the theoretical and practical challenges of the use of AI in pediatrics. Researchers and practitioners can use the results of this study to improve their understanding of the area and can catalyze their further knowledge development. This study can also inform novice researchers, government administrators, interested readers, research managers, and patients without specific knowledge and help them develop a perspective on the most important research dimensions. Finally, the landscape can serve as a guide for further research and as a starting point for more formal knowledge synthesis endeavors like systematic reviews and meta-analyses.

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